Color signals in natural scenes: characteristics of reflectance spectra and effects of natural illuminants

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Multispectral images of natural scenes were collected from both forests and coral reefs to represent typical, complex scenes that might be viewed by modern animals. Both reflectance spectra and modeled visual color signals in these scenes were decorrelated spectrally by principal-component analysis. Nearly 98% of the variance of reflectance spectra and color signals can be described by the first three principal components for both forest and coral reef scenes, which implies that three well-designed visual channels can recover almost all of the spectral information of natural scenes. A variety of natural illuminants affects color signals of forest scenes only slightly, but the variation in ambient irradiance spectra that is due to the absorption of light by water has dramatic influences on the spectral characteristics of coral reef scenes.   © 2000 Optical Society of America [S0740-3232(00)01802-0]

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1. INTRODUCTION

Reflectance spectra are physical properties of materials, which can be utilized as cues to identify different objects. However, the light reaching a visual system is the combination of reflectance and illumination spectra (defined as color signals in the present study). For a long time, color vision has been recognized as having the ability to recover reflectance under various illuminants in order to achieve color constancy.[1–4] Most computational models of color constancy involve the assumption that reflectance spectra of objects can be described by a few basis functions (for a review see Ref. 5). In turn, visual systems with two or more different photoreceptor types are able to estimate the weights of these basis functions and thereby to recover reflectance spectra of objects.[3–6] Therefore the characterization of reflectance spectra is an important step to understanding color vision.

Historically, the properties of reflectance spectra of natural objects were first examined by Krinov.[7] His dataset included 337 surface reflectance spectra of naturally occurring objects. Subsequently, Cohen[8] was the first to apply a linear model to a set of measured reflectance spectra from Munsell color chips to describe the properties of surface spectral reflectances. Based on the analysis of characteristic vectors, he demonstrated that the first three basis functions (characteristic vectors) can account for 99.2% of the total least-squared variation. Since Cohen's analysis used only 150 reflectance spectra chosen randomly from the set of 433 Munsell colors,[9] it is unlikely that these results can be generalized to other sets of surface spectral reflectances in the natural environment with confidence.[10] Maloney[11] has evaluated Cohen's linear model extensively by using the data of surface spectral reflectances from both Krinov's set[7] and Munsell color chips[9] and concluded that five to seven basis functions are required to account for 99.9% of the variance in spectral reflectance. If the sensitivity of the photopic visual system was used to enhance the constraints on reflectance spectra, the number of basis functions can be reduced to 3 or 4.[11,12] The complete set of Munsell color chips (1257 reflectance spectra) has been measured by Parkkinen *et al.*,[13] and they showed that as many as eight characteristic spectra are needed to achieve good representation for all spectra.[13,14] Another set of reflectance spectra from various natural and man-made materials has been recently measured and analyzed by Vrhel *et al.*[15] Their results also indicate that three to seven principal components (PC's) are required to represent more than 99% of the total variation of spectral reflectance. Thus, depending on the choice of subject material, anywhere from three to eight basis functions may be necessary for a full reconstruction of all reflectance spectra.

However, the minimum number of basis functions required to describe reflectance spectra of any set of objects adequately is also determined by the properties of the visual system under consideration. Most investigators used >99% of the total variance represented in basis functions as a criterion,[11,13] but it is not obvious how this statistical criterion may be relevant to perceptual responses. Although the results from analyses of reflectance spectra of Munsell color chips can be used to explain some computational models of color

constancy,[1–5,8,11] Munsell color chips are designed mainly for human color vision, and the relevance of their reflectance spectra to visual systems of other animals is uncertain. Even in Krinov's dataset,[7] the natural objects from which reflectance spectra were obtained are from a variety of different environments. Most animals will not encounter many of these various environments in their lifetimes. In other words, to study animal color vision, one must take into account the reflectance spectra of the natural scenes and the illuminant spectra of natural light that the animals encounter in their own habitats.

In this study we wished to consider complex natural scenes that might be viewed by either terrestrial or aquatic animals. For this purpose we used a multispectral imaging device that can sample reflectance spectra from many locations in a single scene. As a result, the ensemble of reflectance spectra within these natural scenes can be estimated. We characterized these reflectance spectra in forests (terrestrial scenes) and shallow-water coral reefs (aquatic scenes) by using principal-component analysis (PCA) to study their spectral properties and to examine how much spectral information can be described in a few basis functions. This is the first time that reflectance images of underwater scenes have been measured, which allows us to compare reflectance spectra of terrestrial and underwater scenes.

To study the effects of natural illuminants on the spectral properties of color signals in natural scenes, we multiplied five different natural illumination spectra measured in forests and four irradiance spectra computed at different depths in coral reefs by the reflectance spectra of these scenes to form color signals. These spectra of color signals were also characterized by PCA to reveal the effects of different natural illuminants on the properties of color signals in natural scenes.

2. METHODS

A. Imaging Device
A CCD camera (Electrim EDC-1000TE camera, 164 × 191 elements, 8-bit resolution) coupled to a variable interference filter (Optical Coating Laboratory, Inc., semicircular) was used to measure many reflectance spectra within the same imaged scene simultaneously (see also Refs. 16 and 17). A portable computer was used with the camera to control wavelength and exposure time and to capture and store images. The half bandpass of the interference filter of this imaging system is ~15 nm, and 40 frame images can be sequentially captured at 7–8-nm intervals from 403 to 696 nm. These series of 40 images are called multispectral images, which contain information in both the spatial and spectral domains. The reliability of the CCD and the interference filter (e.g., the possibilities of IR contamination, CCD nonlinearity, and spatial distortion) was assessed independently by imaging a known reflectance standard (MacBeth Color Checker) before collecting data in the field. No sign of IR contamination, CCD nonlinearity, and spatial distortion was found in our system. A 16-mm lens (terrestrial scenes) or a 6.5-mm lens (aquatic scenes) was used with the CCD camera, producing corresponding pixel sizes of $0.04° \times 0.055°$ or $0.116° \times 0.136°$ (horizontal × vertical), respectively. Comparisons among images collected at different wavelengths showed no evidence of systematic magnification or registration errors within the resolution of the system.[16] For use underwater the whole imaging system was put into an underwater housing and operated remotely from a surface vessel.

B. Calibration of Reflectance Spectra
To determine the relative reflectance at each pixel, we placed a white standard (Spectralon, 100% diffuse reflectance material, Labsphere) and a black standard (3% spectrally flat diffuse reflector, MacBeth) in one corner of each imaged scene (in both terrestrial and underwater conditions) to serve as comparisons for the overall range of reflectance. Note that the actual reflectances of these objects may have varied somewhat from that of the scene as a whole, depending on their local illumination. While we are not measuring the true reflectance spectra, the data for forest scenes closely approximate reflectances. The data for coral reef scenes may deviate from true reflectances significantly, depending on depth and water quality. Terrestrial images were collected on cloudy days, which increases the reliability of reflectance approximation by reducing the possible effects of shadow. Aquatic images were recorded on cloudy days to remove the flicker effect (wave-induced illumination change) and at close distances (typically less than 1 m) to reduce the effect of water absorption. These precautions help to reduce the error of reflectance approximation.

In each imaged scene, exposure was individually determined at each wavelength to adjust the brightness of the white standard to a level of 220–235 (of a possible 255). Exposures were typically 250–5000 ms in length, and the time required for a complete scan was typically approximately 3–5 mins. Once the series of 40 images was collected, a completely opaque shutter was automatically placed in front of the camera, and a series of images was collected with no illumination to determine the level of dark noise for each exposure series under the conditions of each individual dataset. The image series was then corrected by subtracting each dark frame from each corresponding data frame in succession. Before proceeding with further analysis, we scaled all pixels in the image to relative reflectances by using the values of the white and black standards measured therein.

C. Collections of Multispectral Images
The collections of multispectral images were conducted in terrestrial (temperate woodland, Patapsco State Park, Md., April 1996; subtropical rain forest, dry sclerophyll forest, and mangroves at various locations in Queensland, Australia, October 1996) and aquatic (coral reefs, Great Barrier Reef, near Lizard Island Research Station, Australia, August 1997) habitats for comparison (Fig. 1). The forest scenes were selected to be representative of temperate woodland, subtropical rain forest, sclerophyll forest, and mangroves, containing trees, rocks, herbs, streams, soil, etc. The coral reef scenes were chosen to represent a typical tropical coral reef and comprised a variety of different species of corals (mainly yellow and brown in color). The depth of coral reef scenes is approximately 3–5 m.

D. Characterization of Reflectance Spectra

To characterize the reflectance spectra of natural scenes, we applied a pixelwise PCA to separate the spectral correlations of 40 frame images (varying in wavelength from 403 to 696 nm) for forest and coral reef scenes.   A total of ten forest images or a total of seven coral reef images were combined to represent the ensemble of forest scenes or coral reef scenes, respectively.   Only the central 128 $\times$ 128 pixels of each image were used in the analyses to avoid artificial objects (e.g., the black and white standards) and water space on the top of some images (see Fig. 1).   Thus a total of 163,840 (128 $\times$ 128 $\times$ 10) reflectance spectra of forest scenes and a total of 114,688 (128 $\times$ 128 $\times$ 7) reflectance spectra of coral reef scenes were analyzed in this study.

Figure 1 shows some multispectral images taken from our dataset of forest scenes and coral reef scenes to represent typical reflectance spectra in these environments. Most spectra in forest scenes reflect the properties of leaves and tree bark, as suggested by Lythgoe and Partridge[18] and Osorio and Bossomaier[19] previously.   Reflectance spectra of coral reefs have been smoothed by a low-pass filter (cutoff frequency of 0.2 cycle/nm), which re-

Fig. 1.   Color images of various natural scenes used in our analyses (upper, temperate woodlands of Maryland; middle left, sclerophyll forest of Australia; middle right, subtropical rain forest of Australia; lower, coral scenes of Great Barrier Reef, Australia).   These images were generated by combining three single frames of multispectral images (452, 548, and 649 nm).   Only the central 128 $\times$ 128 pixels in each image were used in actual analyses to avoid including black/white standards and water space in the scenes.
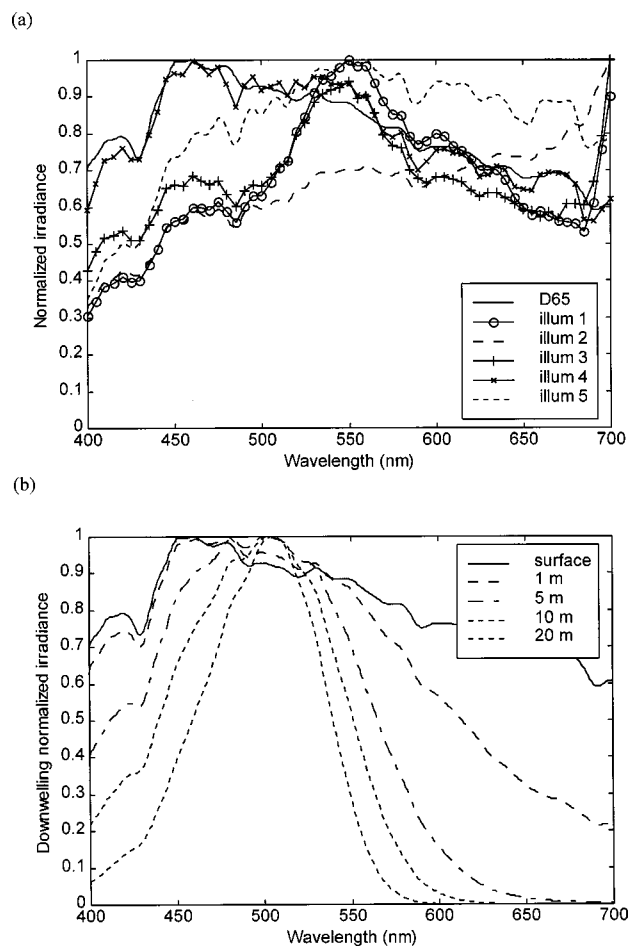
(a)

(b)

Fig. 2.   (a) Normalized irradiance spectra of illumination in forest.   D65 (solid curve) is a CIE standard daylight illuminant. Illuminants 1–5 are natural illuminant spectra measured directly in forests of Australia in 1996.   These natural illuminant spectra can be grouped into four categories according to Endler.[20] For instance, illuminants 1 and 3 represent the light from forest shade, illuminant 2 is the light from small gaps, illuminant 4 is the light from woodland shade, and illuminant 5 is the light from large gaps (see Ref. 20 for details).   (b) Normalized downwelling irradiance spectra at different depths in coral reefs.   D65 (solid curve) is assumed to be an illuminant at the surface.   Downwelling irradiance spectra at 1, 5, 10, and 20 m were computed based on diffuse attenuation coefficients $k(\lambda)$ measured *in situ* [see Eq. (2)].

duces the high-frequency noise caused by fishes swimming by when the images are taken.

E. Effects of Natural Illuminants in Forest Scenes

To determine the effects of natural illumination on the spectral properties of color signals in forest scenes, we used five different natural illuminant spectra measured directly in forests [Fig. 2(a)].   These forest illumination spectra are for light falling through a 90° solid angle aperture onto a horizontal barium sulphate standard. These were recorded by using an S1000 spectroradiometer (Ocean Optics), calibrated by a Clarke-Berry standard (UK National Physical Laboratory).   The illumination was measured throughout the day and at various positions in the canopy and the forest floor.[20]   The CIE standard daylight illuminant D65 (Ref. 21) was also used for comparison.   Reflectance spectra of forest scenes were

then multiplied pixelwise by different natural illuminant spectra to form the color signals $L(\lambda)$ [see Eq. (1)], which represent the visual stimuli from forest scenes:

$$L(\lambda) = I(\lambda)S(\lambda), \qquad (1)$$

where $I(\lambda)$ is the illumination spectrum, $S(\lambda)$ is the reflectance spectrum, and $L(\lambda)$ is the color signal. The units in which $I(\lambda)$ is measured are not important for the purposes of this study. It should be noted that $L(\lambda)$ may depend on the geometry of the scenes, including the angle of incidence of the illuminants on the scenes and the angle between objects and the line of sight. We are concerned here with fixed geometric relations among objects, light sources, and the visual sensor array.

These color signals $L(\lambda)$ of forest scenes were again analyzed by pixelwise PCA to examine whether the spectral characteristics of these forest scenes will be altered by various natural illuminants.

F. Effects of Water Depth in Coral Reef Scenes

To examine the effects of water depth on spectral properties of color signals in coral reef scenes, we used the CIE standard daylight illuminant D65 (Ref. 21) to represent the illumination at the surface, $I_0(\lambda)$. The diffuse attenuation coefficient $k(\lambda)$ of water in coral reefs was taken from Cronin *et al.*[22] Therefore the irradiance spectrum of downwelling illumination at a given depth d, $I_d(\lambda)$, can be directly computed by using Eq. (2) [results are presented in Fig. 2(b)]:

$$I_d(\lambda) = I_0(\lambda)\exp[-k(\lambda)d]. \qquad (2)$$

The color signal $L(\lambda)$ at each depth can in turn be calculated by multiplying the reflectance spectra of coral reef scenes, $S(\lambda)$, by irradiance spectra at different depths, $I_d(\lambda)$, and then analyzed as in Subsection 2.E by pixelwise PCA.

3. RESULTS

A. Characteristics of Reflectance Spectra of Natural Scenes

Nearly 98% of the total variance in the reflectance spectra of both forest and coral reef scenes can be described by the first three PC's, and almost 90% of the variance is concentrated in the first PC (Table 1). These results are consistent with the findings of Cohen,[8] Maloney,[11] Parkkinen *et al.*,[13] and Vrhel *et al.*[15]

The basis functions (characteristic vectors or eigenvectors) of the first three PC's of the ensemble of reflectance spectra from forest and coral reef scenes are plotted in Fig. 3. While the signs of basis functions are arbitrary, a careful comparison of the shapes of basis functions in forest and coral reef scenes (Fig. 3) shows that these functions have subtle differences in form.

B. Effects of Natural Illuminants on Natural Scenes

In forest scenes various natural illuminants have little effect on the results of PCA of color signals $L(\lambda)$. In all illuminants more than 98% of the total variance can be explained by the first three PC's, and almost 90% of the total variance continues to be described by the first PC [Fig. 4(a)]. Furthermore, the basis functions of the first

Table 1. Percentage of Variance Accounted for by the First Four Principal Components (PC's) of Reflectance Spectra in Forest and Coral Reef Scenes

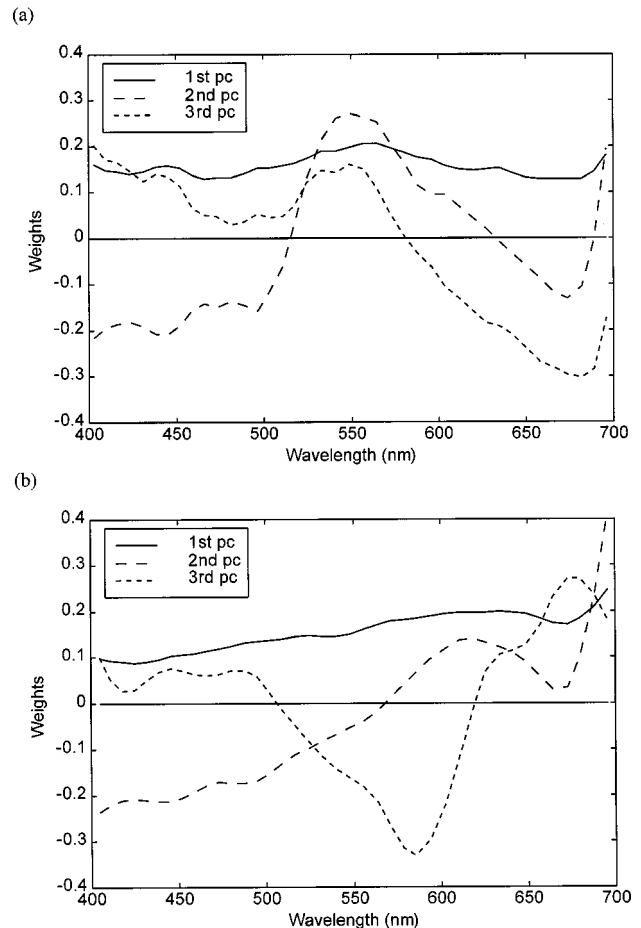| Scene	1st PC	2nd PC	3rd PC	4th PC
Forest	89.2042	5.4875	3.8834	0.5158
Coral Reef	90.4324	4.9586	2.3348	0.8206

Fig. 3. Basis functions of the first three principal components (PC's) from principal-component analysis (PCA) of reflectance spectra of (a) forest scenes and (b) coral reef scenes (same datasets as those in Table 1).

three PC's from color signals of forest scenes are quite similar (Fig. 5), despite the fact that natural illuminants vary a lot spectrally in the forests during the day and between different locations [Fig. 2(a)]. This indicates that a diversity of natural illuminants has little effect on color signals of forest scenes, at least as revealed by PCA.

In contrast, the results of PCA of color signals $L(\lambda)$ of coral reef scenes are dramatically influenced by water depth. On the surface and at 1-m depth, more than 98% of the variance in coral reef scenes can be explained by the first three PC's [Fig. 4(b)]. But as the depth increases, only two (5 and 10 m deep) or even one (20 m deep) PC is sufficient to describe almost 98% of the total variance. The changes of illumination spectra with

depth also constrain the forms of the major PC's in coral reef environments. The basis functions of the first PC of the color signals of coral reef scenes change from very flat at the surface [Fig. 6(b)] to a narrow band at 20 m deep [Fig. 6(f)].
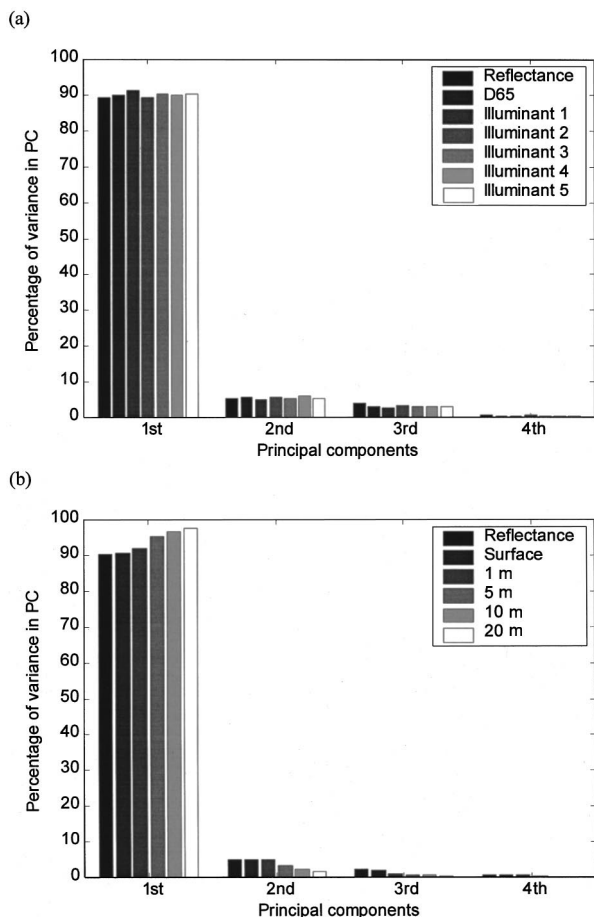
(a)

(b)

Fig. 4. Percentages of the total variance in the first four PC's from PCA of color signals of (a) forest scenes and (b) coral reef scenes under the different illuminants illustrated in Fig. 2.
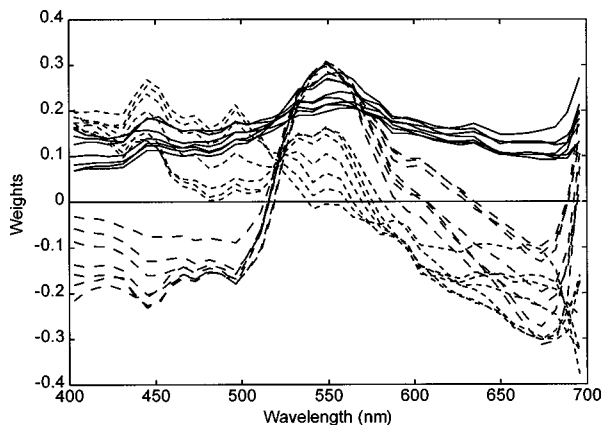

Fig. 5. Basis functions of the first three PC's from PCA of color signals of forest scenes under various illuminants. Solid curves, the first PC's; long-dashed curves, the second PC's; short-dashed curves, the third PC's.
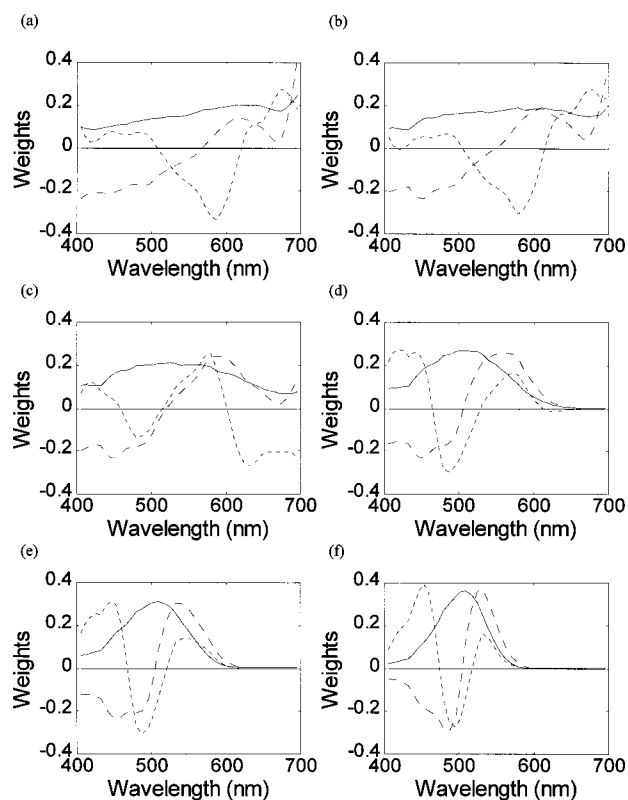

Fig. 6. Basis functions of the first three PC's from PCA of color signals of coral reef scenes at different depths [Fig. 2(b)]: (a) results from analyses of reflectance spectra of coral reef scenes only, and results from analyses of color signals at (b) the surface, (c) 1 m, (d) 5 m, (e) 10 m, and (f) 20 m. Solid curves, the first PC's; long-dashed curves, the second PC's; short-dashed curves, the third PC's.

4. DISCUSSION

Reflectance spectra of natural objects have been measured for at least 50 years, beginning with Krinov.[7] While he extensively collected reflectance spectra of natural materials, the spectral range of his dataset falls within 400 and 650 nm, at 10-nm intervals, and for some materials some data points are missing even within this range (as pointed out by Vrhel *et al.*[15]). Besides, Krinov's dataset is limited to terrestrial environments, which excludes other interesting habitats, in particular the aquatic environment. With the imaging device employed in this study, we can simultaneously collect 31,324 reflectance spectra with an extended spectral range (400–700 nm) and a shorter spectral interval (7–8 nm). In addition, some reflectance spectra collected from the variety of different natural objects, man-made materials, and Munsell color chips in previous studies (e.g., Refs. 11 and 13–15) will never be encountered by animals in their natural life. Using our multispectral imaging device, we can collect images from the scenes that animals may see in their natural environments (both terrestrial and aquatic habitats). One would expect these datasets to be more meaningful in the study of the evolution and the design of animal color vision.

Though we went to some efforts to avoid uneven illumination (e.g., recording images on cloudy days to eliminate shadows) during image collection, there are still other fac-

tors (e.g., internal reflections from foliage) that influence our measurements, making them only general approximations of the true reflectance spectra of all objects in the scene. Nevertheless, these approximations are close enough to represent real reflectance spectra in natural scenes. Separating illuminant spectra and reflectance spectra in multispectral images remains a difficult challenge when collecting data from natural scenes. In future work we hope to characterize the spatial variation of illumination in natural scenes.

Characterization of reflectance spectra of natural scenes by using PCA is one way to decorrelate the spectral information into fewer uncorrelated components. If each visual channel can sample these components independently, the number of visual channels for reconstructing the reflectance spectra can be reduced. This approach has embedded an assumption of redundancy reduction[23,24]; that is, visual systems should remove redundancy in visual stimuli to achieve efficient neural coding. Based on the PCA results of reflectance spectra collected from two different types of natural scenes, we confirmed that three basis functions are sufficient to describe 98% of the total variance in the scenes and that 90% of this variance can be described by the first PC alone. These results suggest that three well-designed visual channels can recover almost all spectral information in natural scenes.[2,11,25]

Although the percentage of the total variance of the third PC in forest scenes is less than that of the first two PC's, the information present in this component might be important biologically. A good example of this biological importance is illustrated by the red–green channels of primate vision. The percentage of the total variance of the third PC [suggesting red–green variation in Fig. 3(a)] in forest scenes is only 3.88%, but the benefit of having the third visual channel in the visual system to extract this part of the information may be crucial for primates to find and discriminate ripe fruits.[26] Since PCA is designed to maximize the total variance accounted for by the first few PC's in the whole dataset, rare but very important biological signals may be missed in such an analysis. Therefore, to study animal vision systems, one has to know the visual tasks that animals perform.[18]

While the ensembles of reflectance spectra of ten individual forest images and seven coral reef images were considered in this study, each scene has been analyzed by pixelwise PCA individually (results not shown). The variation within each class of environment (terrestrial or aquatic) is small. For example, there is no great difference between the Maryland and Australian scenes, and there are only slight differences among the various coral reef environments. Nevertheless, in each individual scene, nearly 98% of the total variance can be explained by only the first three PC's.

Any visual signal reaching a visual system is the combination of illumination and reflectance spectra. In this study we investigate the effects of natural illuminants on the properties of spectral information. As the PCA results from color signals of forest scenes show [Figs. 4(a) and 5], there is little difference in the number and the forms of basis functions required to recover 98% of the total variance, even in quite variable illumination conditions. This indicates that the spectra of natural illuminants affect the spectral properties of forest scenes only slightly.

However, in the case of coral reef scenes, water absorption plays a significant role,[27] making the broad spectrum of daylight on the surface become more and more narrow as the depth increases. As the PCA results of color signals in coral reef scenes show [Figs. 4(b) and 6], there are dramatic differences in the number and the forms of basis functions required for describing 98% of the total variance among images illuminated at different depths. The deeper the water, the less chromatic variation present in the scenes. The significant constraints of natural illuminants on spectral properties of aquatic scenes indicate that the amount of color information is altered and drastically reduced with increasing depth. Color constancy is probably more difficult to achieve underwater than on land. This is because spectrally selective absorption by water leads to changes in illumination with depth and water quality. Besides this, there are additional spectral effects of viewing distance, a consideration that is usually negligible on land.[28,29]

In summary, we collected and characterized multispectral images of natural scenes by using principal component analysis and confirmed that three basis functions are sufficient to describe nearly 98% of the spectral variation of both reflectance spectra and color signals in natural scenes. Furthermore, we examined the effect of natural illuminants on color signals in natural scenes and concluded that variations in natural illuminants have little effect in terrestrial environments but dramatically influence spectral properties in aquatic environments. These findings may have implications regarding the design of visual systems of terrestrial and aquatic animals.

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